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Tulu Manuscript OCR: Preserving Ancient Wisdom through Character Recognition

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***Abstract*—Tulu, largely spoken in coastal Karnataka, has a distinct alphabet that used to be written on palm leaves. This study addresses the scarcity of efficient OCR solutions. Employing machine learning algorithms that include decision tree, k-nearest neighbors (KNN), and random forest. The system achieves its highest accuracy of 92.35% with the random forest algorithm. The system's versatility in handling diverse font styles and sizes is crucial for Tulu character recognition. The inclusion of a classifier-level fusion strategy enhances recognition accuracy, which is vital given the intricate nature of Tulu characters. This research advances OCR technology for Indian languages, specifically meeting the unique needs of the Tulu script. The effectiveness of the random forest algorithm, achieving high accuracy, underscores its potential for broader applications. The proposed Tulu Character Recognition System represents a pivotal step in addressing the OCR gap for Indian languages, holding promise for future linguistic technology advancements.**

Keywords—optical character recognition (OCR), tulu character recognition system, classifier - level fusion strategy.

I. INTRODUCTION

Tulu is Dravidian & agglutinative language predominantly spoken in India's coastal areas of Kerala and Karnataka, meaning that grammatical and syntactic information is conveyed by appending affixes to the root words. This feature gives the language more accuracy and flexibility. Tulu manuscripts include a wide range of topics, from literature and philosophy to astrology and medicine. They are frequently transcribed on palm leaves or parchment [3 4]. These manuscripts provide priceless insights into the cultural and historical context of the Tulu-speaking regions in addition to acting as archives of traditional knowledge [4] [5]. As far as it is known, Tulu inscriptions date to the seventh and eighth centuries AD. These Tulu-script inscriptions may be seen in and around Barkur, the former Vijayanagara capital of Tulu Nadu. In the vicinity of Kundapura, at the Ullur Subrahmanya Temple, is another set of inscriptions. According to linguists like L. V. Ramaswami Iyer, S. U. Panniyadi, P. S. Subrahmanya, and others, Tulu, having split out from its Proto-Dravidian roots around 2500 years ago, is one of the oldest languages in the Dravidian family. This claim is supported by the fact that Tulu still exhibits several Proto-Dravidian language features.

The preservation of traditional wisdom has become critical in a society were digital revolutions and technical breakthroughs are pervasive [9]. The need of creating Optical Character Recognition (OCR) especially for Tulu manuscripts stems from the pressing requirement to preserve and make available the priceless information contained in these fragile, handwritten pages [1][2][6][10]. There's a growing danger of losing this rare information as these manuscripts disintegrate with age. The Tulu Manuscript OCR effort is driven by two goals: first, to preserve the rich cultural history that these manuscripts hold, and second, to make their abundance of information widely accessible. Preserving old wisdom is essential to closing the gap between the past and the future, not just a nostalgic endeavour [1][3]. Manuscripts from Tulu act as time capsules, preserving the customs, values, and academic interests of earlier times. Also make sure that these manuscripts are not lost to deterioration and neglect by creating an OCR system that is especially suited to the nuances of the Tulu script [2][3][7]. OCR technology makes transcribing faster, more accurate, and more widely available by automating the process.

The lack of comprehensive datasets and codes is a serious barrier for academics attempting to expand and repeat Tulu script recognition results. The paucity of resources makes it difficult to design and enhance recognition models that are customized to the intricacies of Tulu handwriting. The primary obstacle these days is the scarcity and digitizing of manuscripts [1] [3] [7]. Tulu's distinctive script adds to the study landscape's complexity. The sheer number of scripts and their intrinsic variability make it difficult to create generic models that can adequately handle Tulu characters. Each screenplay may have unique characteristics, making it challenging to develop a one size-fits-all solution [36]. Considering the variety of writing styles and quirks found in Tulu script. Overcoming this obstacle is critical for training recognition models capable of properly interpreting and transcribing handwritten Tulu text.

The preservation and accessibility of Tulu manuscripts have been restricted by a number of issues, despite their cultural significance [7]. Conventional preservation techniques, like transcription by hand and conservation initiatives, are costly, time-consuming, and error-prone [8]. Furthermore, the difficulty of effectively decoding and comprehending these manuscripts is further compounded by the lack of specialists skilled in the Tulu script. Previous attempts to digitise Tulu manuscripts using general OCR technologies have not produced the best results because of the special features and complexity of the script. The Tulu Character Recognition System research significantly contributes to preserving ancient Tulu manuscripts through an advanced OCR system. A manual collection of a comprehensive dataset with 54 Tulu characters showcases the system's versatility in handling diverse fonts. The inclusion of a classifier-level fusion strategy enhances recognition accuracy for intricate Tulu characters. Acknowledging limitations, the research paves the way for future OCR advancements in Indian languages. The proposed Tulu Character Recognition System, addressing the unique needs of the Tulu script, is a pivotal step in bridging the OCR gap for regional languages, promising broader applications and continued linguistic technology development.

The remaining portion of this paper is organised as follows: Section 2 of this paper presents a comprehensive literature review of related works done in preserving Tulu manuscripts. The approach used in this paper for creating datasets, preparing data, augmenting data, and binarizing data is described in Section 3. In Section 4, the performance of the suggested OCR system is discussed and the experimental results are presented. The paper is finally concluded in Section 5 with a summary of the results and future scope.

A. *Literature survey*

In [24], The research employs a hybrid method, integrating structural and statistical techniques, to recognize the Tulu script with an accuracy of 88.5%. However, the study is limited by a small dataset size, primarily composed of historical documents, which may restrict the model's generalizability. Moreover, handwritten text variations beyond the scope of the training data could pose challenges to the effectiveness of the method in real-world applications.

In [37], the OCR system utilizes image preprocessing to enhance clarity, followed by feature extraction to capture characteristics like edge information. Templates are compared with extracted features using techniques such as cross-correlation for character recognition. Despite achieving 80.5% accuracy, challenges persist in recognizing characters accurately, particularly those with subtle differences. Future enhancements aim to improve recognition accuracy and address limitations.

In [38], The paper employs Haar features and AdaBoost algorithm for Tulu script recognition, mapping it to Kannada. MATLAB R2014a facilitates implementation. Results exhibit recognition accuracy analyzed through precision and recall, particularly for vowels and consonants. Challenges involve limited datasets, impacting robust training. Binarization struggles with degraded paper quality. Character segmentation complexity arises from diverse handwriting styles. Efficient feature extraction, though based on Haar features, may encounter difficulties in capturing nuanced Tulu script distinctions, warranting further research.

In [39], The study employs a convolutional neural network (CNN) architecture for Sanskrit OCR, overcoming challenges through data augmentation and pre-processing techniques. Limitations include the need for extensive training data and the inability to handle extremely degraded text. Despite these constraints, the system achieves promising results, demonstrating high accuracy in character recognition and outperforming traditional methods. Future work aims to address remaining challenges and improve performance on degraded manuscripts.

Effective text extraction is a key component of this recognition system, and recent work has explored a number of techniques. As mentioned in [11], Otsu thresholding is a well-liked method for binarization among them. Recognizing the shortcomings of Otsu thresholding alone in terms of noise and character degradation, however, [12] investigates more sophisticated binarization methods. In order to improve character recognition, these methods combine adaptive contrast mapping, Otsu thresholding, and intelligent edge detection.

In [20], The research utilized image preprocessing and Convolutional Neural Networks for Kannada handwritten character recognition. Achieved a 95.11% training set accuracy and 86% testing set accuracy. Limitations include variability in handwriting styles affecting accuracy and computational complexity, with potential improvement through GPU utilization and hybrid algorithm development.

Segmentation techniques post-binarization are crucial, emphasized in [13] and [14]. [13] employs basic projection profile analysis for line and character segmentation, while [14] introduces a method for text line segmentation based on previous line estimations. Additionally, [15] investigates character segmentation using linked component analysis and projection profile combination, simplifying isolation for in-depth examination. Feature extraction is crucial for efficiently understanding both local and global information in a character picture. A wavelet-based method for feature extraction is described in recent work, such [16], highlighting the significance of collecting data at various sizes. Furthermore, [17] provides a large dataset for analysis by using a hybrid approach to get projection features and inertia moment characteristics.

After feature extraction, both supervised and unsupervised methods train character recognition models. An unsupervised approach, detailed in [19], utilizes K-means clustering for pattern recognition and character grouping without specific training data. Moreover, [18] explores supervised learning models trained on characteristics from the Tulu script, involving both purposeful and passionate learners.

II. METHODOLOGY

Creating a machine learning model for Tulu character recognition involves several crucial processes are shown in Fig 1, each playing a pivotal role in achieving accurate and reliable results.

- Tulu Dataset Collection: Acquire a diverse set of Tulu characters from manuscripts to form the foundation of the model, ensuring a comprehensive and varied dataset that captures the intricacies of the language.
- Data Retrieval: Organize and save collected pictures for further processing, guaranteeing dataset accessibility and effective management in subsequent stages.
- Data Preprocessing: Enhance dataset quality by cleaning, resizing, and standardizing photos, addressing anomalies, and providing a well-prepared and consistent dataset.
- Gray Scaling and Normalization: Preserve crucial character information by converting photos to grayscale while normalizing scale pixel values to

ensure uniform ranges for optimized machine learning algorithm learning.

- Binarization: Streamline visuals by reducing graphics to black and white, highlighting character boundaries, improving contrast, and preparing data for feature extraction and analysis.
- Feature Engineering: Define features for model identification, such as corners, stroke patterns, or other distinguishing characteristics, by selecting and deriving relevant data from binarized images.
- Principal Component Analysis (PCA): Reduce dimensionality using PCA to keep important information, mitigate the curse of dimensionality, enhance computing efficiency, and facilitate successful model training by identifying major components.
- Model Training: Use machine learning algorithms like Random Forest, Decision Tree, and Support Vector Machine to train the model, identifying correlations and patterns in Tulu character images.
- Model Assessment and Fine-tuning: Assess model performance using metrics like F1 score, accuracy, precision, and recall. Fine-tune features, hyperparameters, and model architecture iteratively to improve performance.
- Model Deployment: Integrate the trained model into systems for practical applications, such as Tulu manuscript identification.

Re-iterate Until Satisfactory Model Performance: Repeat the procedure as needed, making adjustments to preprocessing stages, feature engineering, or algorithm selection until achieving a high enough degree of accuracy and dependability in Tulu character recognition. This iterative process ensures continuous improvement and adaptation to linguistic challenges.

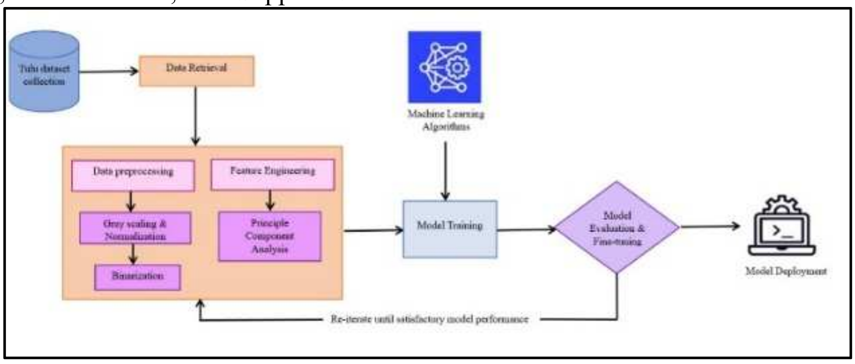

Fig. 1. Model Architecture

A. Data Collection Process

When a pre-existing dataset that met our requirements wasn't easily accessible, we took a hands-on approach to creating a custom handwritten Tulu dataset. Working with those who actively supported this project, the assignment was carefully drawing Tulu figures on regular A4 sheets, with each character being 30 cm wide and 30 cm tall. Black marker pens were specifically chosen in order to guarantee the best possible legibility and clarity of the drawn characters. The handwritten sheets' organisational structure was meticulously matched to our dataset's predefined structure, bringing a methodical and uniform approach to the data collection procedure. There was more control over the calibre and variety of the assembled Tulu figures thanks to this manual assembling[20].

The next stage was to digitise the handwritten Tulu sheets after the manual creation process was finished. Every sheet was carefully scanned, and the JPG format was used to store the final photos. This format was selected to strike a compromise between effective storage and transmission and crucial image quality for accurate character recognition. We were able to successfully compile a large dataset with a total of 50,400 photographs by using this methodical technique. As of right now, this custom dataset is a useful and influential tool that will likely have a big impact on future research on handwritten script recognition and Tulu character recognition systems. This dataset is a fundamental component of our project, as seen by Fig.2, the Handwritten Tulu Character Dataset.

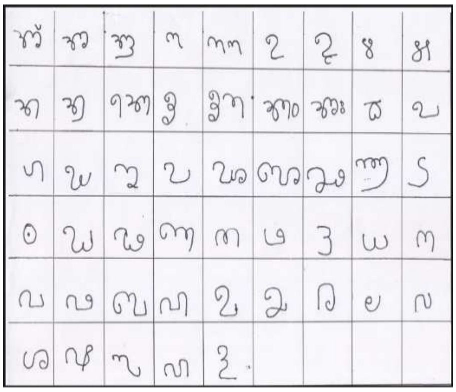

Fig. 2. Collected Handwritten Tulu Characters

B. Preprocessing of Dataset

In the realm of machine learning, the process of preparing images for model training and inference is commonly referred to as preprocessing. To accomplish transformation, several preprocessing procedures are applied, including thinning, noise reduction, and binarization [21] [22]. This crucial step is undertaken to optimize the quality and uniformity of the input data, ensuring that the machine learning model can effectively learn and make accurate predictions. The key components of image preprocessing include resizing, orientation standardization, and color adjustments [23].

1) Resizing for Standardized Dimensions: Standardizing image dimensions through resizing is crucial for model training, promoting uniformity and enhancing the model's ability to generalize patterns effectively.

2) Consistent Orientation: Standardizing the orientation of images is crucial for eliminating potential variations caused by differences in how images are captured or presented. Ensuring that all images have a consistent orientation aid in creating a more predictable and stable dataset, contributing to the model's ability to learn reliably.

3) Colour Adjustments for Clarity: Colour adjustments are implemented to enhance the overall quality and clarity of the images. This may involve converting images to grayscale or applying normalization techniques. The objective is to reduce the impact of colour variations that may not be critical for the specific task at hand, simplifying the image representation for the model.

By performing these preprocessing, the images are refined to meet the specific requirements of the machine learning model. This optimization is fundamental in mitigating potential challenges and variations that could impede the model's performance during training and inference. Ultimately, a well-preprocessed dataset contributes to the model's robustness, ensuring it can generalize well to new, unseen data and make accurate predictions in real-world scenarios.

C. Applying Grayscale

In the context of grayscale pre-processed images, the script systematically extracts characters and arranges them into a well-structured directory. It sequentially processes images within the designated main folder, determining cell dimensions based on specified rows and columns, and subsequently extracting characters accordingly. These characters are systematically catalogued in a dictionary, organized by their respective row and column positions. Following this, the script establishes a directory hierarchy, storing grayscale characters in folders corresponding to their specific row and column coordinates. This systematically organized directory proves advantageous for subsequent tasks, such as Optical Character Recognition (OCR) training, as it preserves the spatial relationships among characters, enhancing the effectiveness of the learning process.[24]. The dataset's grayscale photos are shown in Fig 3.

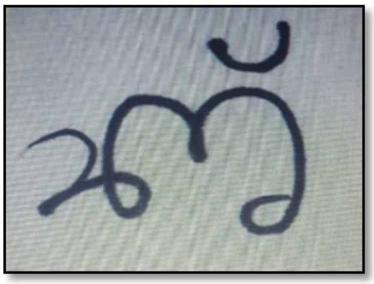

Fig. 3. Grayscaled Image for tulu character

D. Binarization

Binarization is the process which converts the images to binary images [8] [25] [26] [27] [28] [29] which is an essential step for effective preprocessing in optical character recognition (OCR) projects[30]. Each image in this procedure is opened one after the other, turned to grayscale, and then binarized using a user-defined threshold [31][32]. An output directory is where the binarized images are methodically kept after being generated[33]. Interestingly, the script can manage several photos arranged in subdirectories of the main directory while maintaining a parallel structure in the output folder. This methodical technique simplifies the binarization of a variety of grayscale character pictures, fully preparing them for further OCR training or analysis procedures. As depicted in Figure 4, the visual representation illustrates the formation of binary images through our applied binarization process.

The dataset's binarized photos are shown in Fig 4.

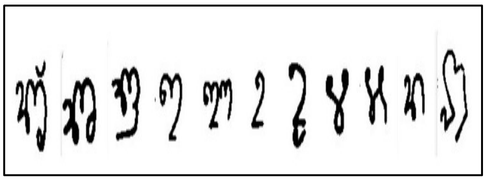

Fig. 4. Binarized Image for Tulu character

E. Augmentation

The subsequent phase involves image augmentation through translation and slant operations, a crucial step aimed at enriching dataset diversity in preparation for Optical Character Recognition (OCR) tasks. The systematic processing of images within a specified input folder includes the application of both left and right translations, introducing variations in positional aspects. Following this, left and right tilts are implemented on the translated images, generating additional instances with varying slant ranges. The resulting augmented images are systematically saved in an organized output folder, preserving the original dataset structure. This augmentation process is meticulously crafted to bolster the robustness and diversity of the dataset, ultimately contributing to the enhanced training and performance of OCR models. Users retain the flexibility to tailor the input folder path and output folder for augmented images based on their specific dataset requirements. The dataset's augmented photos are shown in Fig 5.

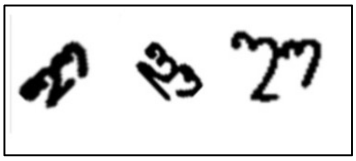

Fig. 5. Data Augmentation for characters

F. Training

We use normal computing resources in our OCR effort; specifically, we train the Tulu dataset on our laptops and PCs. We optimize our methodology to attain significant outcomes while adhering to the limitations of the accessible computing infrastructure. Table 1 provides a detailed description of our experimental setup, including the tools we employed.

TABLE I. DETAILS OF EXPERIMENTAL PLATFORM

Hardware Platform		**Software Platform**	
CPU	Intel Core i5 1240P CPU @1.70GB	OS	Windows 11 64 bit
RAM	16.0GB	Framework	OpenCV
		Programming	Python

G. Testing

The model that was previously trained on the training data is evaluated using the test data to determine the prediction scores for each class. Prediction scores for every class are produced by applying the model's predictive power to the test dataset. The most likely estimation for the relevant class in the test data is then determined by tallying the prediction scores of all the classes. This method contributes to a more nuanced understanding of the model's effectiveness in practical applications by enabling a thorough evaluation of the model's performance in classifying and predicting classes based on the features included in the test dataset.

III. Result and Discussion

In the testing stage, machine learning models were thoroughly assessed using accuracy measures to determine their predictive abilities. These models included K-Nearest Neighbors (KNN), Random Forest, Decision Trees, Logistic Regression, Linear Regression, and Naïve Bayes. In the comprehensive evaluation of our Tulu Optical Character Recognition models, the Random Forest model demonstrated superior performance with an accuracy of 92.35%, Decision Tree 89.38%. While other machine algorithms showed comparatively less accuracy, they are Logistic Regression 60.81%, Linear Regression 0.2% and Naïve Bayes 11.28% models. This outcome underscores the efficacy of the Random Forest approach in capturing intricate Tulu character patterns, positioning it as a promising choice for further refinement and practical deployment in real-world OCR applications.

Random Forest showed robustness despite interpretability issues, Decision Tree and KNN proved effective in non-linear settings with huge datasets. While Logistic Regression was computationally efficient, it required linearity. Because of the simplicity, linear regression may not be as good at capturing non-linear patterns. Computationally efficient Naïve Bayes model assumes independence of features. The evaluation, which is presented in Table 2, includes training and testing accuracy. This allowed for a more nuanced understanding of the benefits and drawbacks of each model.

TABLE II. Accuracy Of All 6 ML Models

Machine learning models	Training accuracy	Testing accuracy
Linear Regression	0.25	0.2
Logistic Regression	0.7934	0.6081
K-Nearest Neighbors	0.8981	0.7016
Naïve Bayes	0.1173	0.1128
Decision Tree	1.000	0.8938
Random Tree	1.000	0.9235

A. Visualizations and Graphs of Model Performance

A more comprehensive knowledge of the advantages and disadvantages of any machine learning model is made possible by the thorough analysis of accuracy measures. A wealth of information about the differences in performance between various paradigms can be gained from the graphs and visualisations that go along with the evaluation of models like K-Nearest Neighbours (KNN), Decision Trees, Random Forest, Logistic Regression, Linear Regression and Naïve Bayes. This analytical method lays the groundwork for determining which model works best and provides guidance on possible improvements to improve predictive power.

The accuracy comparison of different models' graph is shown in Fig 6.

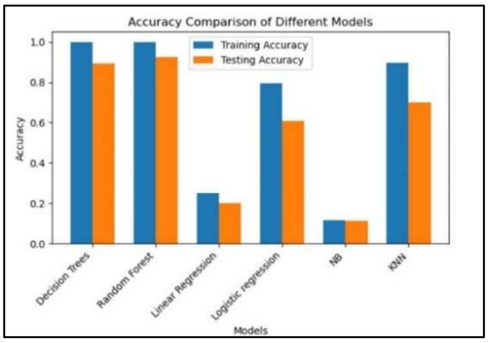

Fig. 6. Visualization graph of various model performance

B. Training and Testing curves obtained

An important part of the research process that offers a thorough understanding of how different machine learning paradigms work is the training and testing phase. Many models are thoroughly tested for their ability to predict outcomes, such as K-Nearest Neighbours (KNN), Random Forests, Decision Trees, Logistic Regression, Linear Regression and Naïve Bayes. The research entails a thorough analysis of accuracy metrics for every model, enabling a deep comprehension of their unique advantages and disadvantages. Using this analytical method helps identify the best model and sets the stage for future improvements to accurately calibrate predictions. The Receiver Operating Characteristic (ROC) curve that was obtained for the evaluation of the models is shown in Fig.7.

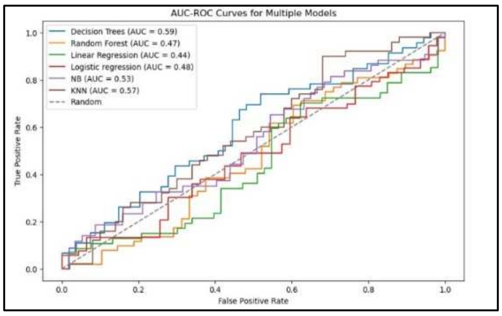

Fig. 7. ROC Curve for ML Models

C. Confusion Matrix

In our Tulu Optical Character Recognition (OCR) research, the confusion matrix a crucial evaluation metric acts as a thorough tool for assessing the effectiveness of two best performing models, Random Forest and Decision Tree. This matrix provides a comprehensive view of the classification accuracy of each model by carefully detailing the number of true positives, true negatives, false positives, and false negatives for each model. The confusion matrices for Random Forest and Decision Tree are shown in Fig 8 and Fig 9. These visual aids offer a comprehensive analysis of the models' performance, showcasing their precision in categorising Tulu characteristics and providing insightful information for future optimisation, so augmenting our comprehension of their efficacy in real-world applications.

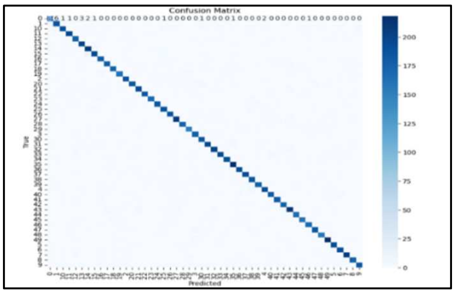

Fig. 8. Confusion matrix for Random Forest

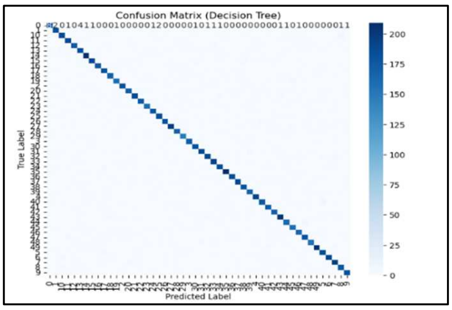

Fig. 9. Confusion matrix for Decision Tree

D. Model deployment

In the last stage of our project, we created an interactive webpage with the Streamlit framework to improve user interaction while our machine learning model is being deployed. This webpage, designed to make the process of uploading images easier, offers a smooth interface through which users can interact with our random forest model that has been deployed. A random forest model was purposefully chosen due to its reliable performance and versatility in a range of environments.

When visitors upload photos, the implemented model quickly determines if the photos can be found, effectively handling the incoming data. This deployment highlights the interface's ease of use while simultaneously demonstrating the trained model's practical applicability in real-world circumstances. It highlights how simply accessible online applications can incorporate machine learning capabilities, highlighting the accessibility of cutting edge technology.

This method not only improves the user experience but also highlights how our project's results are applicable in the real world. The Tulu Optical Character Recognition (OCR) Streamlit application makes it simple for users to input photos, view the model's predictions, and examine both the original and processed images as well as the related OCR results, labels, and filenames. In addition to offering a visual representation of labelled photos, the featured dataset images enhance the user experience by allowing for an interactive and informative interaction with the OCR model's predictions on Tulu characters. The model deployment image is depicted in Fig 10.

Fig. 10. OCR application deployed

E. Discussion

The research tackles the challenge of limited Optical Character Recognition (OCR) solutions for the unique Tulu script in coastal Karnataka, achieving an impressive 92.35% accuracy using machine learning algorithms like decision tree, k-nearest neighbors (KNN), and random forest. Emphasizing the importance of preserving Tulu manuscripts on palm leaves for cultural and historical insights, the study addresses challenges such as scarce datasets and the intricate nature of Tulu script. The proposed Tulu Character Recognition System, featuring a classifier-level fusion strategy, significantly contributes to manuscript preservation. The paper outlines the methodology, experimental setup, and model performance, highlighting the Random Forest model's effectiveness. The research concludes with the OCR model deployed in an interactive webpage, demonstrating practical utility. While recognizing limitations, the study recommends future work for character set expansion, recognizing multiple characters, and collaborating with linguists for deeper contextual insights. Overall, the research holds promise for advancing OCR technology in Indian languages, particularly for safeguarding Tulu manuscripts.

IV. CONCLUSION

In conclusion, the current research has made substantial progress in the preservation of ancient Tulu manuscripts through the development and deployment of an optical character recognition (OCR) system. The manual collection of the Tulu dataset and the application of rigorous data preprocessing techniques were pivotal steps in ensuring the accuracy and reliability of the machine learning model. The successful training and deployment of the OCR model, particularly with the Random Forest algorithm achieving a commendable accuracy of 92.35%, underscore the efficacy of the methodologies undertaken. The certain limitations must be acknowledged. The current research is confined to a limited set of applicable characters, and the recognition is restricted to one character at a time. The requirement for uniform pixel sizes in images impacts the system's accuracy, posing a constraint on the diversity of Tulu manuscripts that can be effectively processed. Additionally, the time complexity involved in training the model presents a challenge, particularly as the dataset or the complexity of the script expands. Looking forward, the future scope of this research is promising. The project can evolve into a more comprehensive platform by addressing the recognized limitations. Future work could involve expanding the character set and enhancing the system to recognize multiple characters simultaneously, thereby improving the efficiency and practical applicability of the OCR system. Moreover, exploring techniques to mitigate the impact of uniform pixel size requirements and optimizing the training process for reduced time complexity would further enhance the system's robustness. Furthermore, the research can extend its reach by incorporating more advanced machine learning models or deep learning architectures to capture even subtler nuances within the Tulu script. Collaboration with linguists and historians could provide valuable insights into historical variations, enriching the contextual understanding of the characters.

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